Short Selling Efficiency

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Abstract

Short selling efficiency (SSE), measured each month by the slope coefficient of cross-sectionally regressing abnormal short interest on a mispricing score, significantly and negatively predicts stock market returns both in-sample and out-of-sample, suggesting that mispricing gets corrected after short sales are executed on the right stocks. We show conceptually and empirically that SSE has favorable predictive ability over aggregate short interest, as SSE reduces the effect of noises in short interest and better captures the amount of aggregate short selling capital devoted to overpricing. The predictive power is stronger during the periods of recession, high volatility, and low public information. In addition, low SSE precedes the months when the CAPM performs well and signals efficient market. Overall, our evidence highlights the importance of the disposition of short sales in stock markets.

Keywords: Short selling efficiency, return predictability, mispricing, market efficiency
JEL Classification: G11, G23

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1. Introduction

Short selling is an essential activity in modern financial markets. The impact of short selling has received wide attention. A large literature examines the effects of short selling on expected stock return both theoretically and empirically.[1] Existing studies identify a significant cross-sectional relation between short selling and stock returns. In contrast to rich evidence in the cross-section, little is known about the time-series relation of short selling to aggregate returns. Rapach, Ringgenberg, and Zhou (2016), as one important exception, show that aggregate short selling can predict stock market returns. Their analysis, however, does not distinguish between short sales executed on different stocks. In this paper, we combine the information of short sales with stock mispricing to examine the role of short selling efficiency in the stock market.

Efficient short selling means that scarce resources for short sales are allocated to overpriced stocks—the place where investment opportunities exist. Motivated by this economic insight, we measure short selling efficiency (SSE) by the slope coefficient of a cross-sectional regression. Each month we regress abnormal short interest (i.e., the ratio of shares sold short over shares outstanding) on the mispricing score of Stambaugh, Yu, and Yuan (2015) constructed from stock anomalies. By computing the covariance between abnormal short interest and overpricing across stocks, the slope coefficient captures the efficiency of short selling. The higher the slope coefficient is, the more short-sales are placed on the right stocks (i.e., more overpriced stocks). Following the intuition in Hanson and Sunderam (2014), to the extent that short sellers are informed about mispricing, SSE recovers information about the amount of aggregate short-selling capital devoted to overpricing. Repeating the regression each month, we obtain a time-series measure of short selling efficiency used for forecasting future stock market returns in our empirical analyses.

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[1] The studies on the effects of short selling and its constraints on stock prices in the cross-section are too voluminous to list in the present paper. For theoretical work, see, e.g., Miller (1977), Harrison and Kreps (1978), Diamond and Verrechia (1987), Duffie, Garleanu, and Pedersen (2002), Hong and Stein (2003), Scheinkman and Xiong (2003), and Hong, Scheinkman, and Xiong (2006). For empirical work, see Asquith and Meulbroek (1995), Danielsen and Sorescu (2001), Desai, Ramesh, Thiagarajan, and Balachandran (2002), Geczy, Musto, and Reed (2002), Jones and Lamont (2002), Christophe, Ferri, and Angel (2004), Ofek, Richardson, and Whitelaw (2004), Asquith, Pathak, and Ritter (2005), Nagel (2005), Bris, Goetzmann, and Zhu (2007), Cohen, Diether, and Malloy (2007), Boehmer, Jones, and Zhang (2008), Diether, Lee, and Werner (2009a, 2009b), Engelberg, Reed, and Ringgenberg (2012), Blocher, Reed, and Van Wesep (2013), Boehmer, Jones, and Zhang (2013), Boehmer and Wu (2013), Hanson and Sunderam (2014), Drechsler and Drechsler (2016), Jones, Reed, and Waller (2016), and Hwang, Liu, and Xu (2019), among others. See Reed (2013) for a survey of the short selling literature.

We first document strong predictive power of SSE for stock market returns both in-sample and out-of-sample over the sample period 1974 to 2017. When regressing future excess stock market returns on SSE at a monthly frequency, we obtain a regression coefficient of -0.61 (t-value = -3.50) and an R^2 of 1.64%. The predictive power persists over one year. At the 12-month forecasting horizon, the regression coefficient is -0.40 (t-value = -3.69) and the R^2 is 8.49%. The predictability is not subsumed by controlling for the aggregate short selling level (SSL) and other market return predictors, suggesting that SSE contains distinct information about future market returns. While the results are robust to various forecasting horizons, SSE predicts stock market returns particularly well over short horizons, suggesting that efficient short selling signals active arbitrage activity and fast price correction. Our out-of-sample tests, following Campbell and Thompson (2008) and Goyal and Welch (2008), confirm that SSE has favorable forecasting ability over the historical average of market returns. The out-of-sample results are robust to imposing alternative economic restrictions about the sign and value of the predicted equity premium. In addition, the predictive power of SSE holds in a battery of robustness tests, including an alternative measure of SSE, the choice of detrending, alternative sample filters, controlling for other drivers of short selling, excluding the financial crisis period, and a bootstrap exercise.

We next digest the results by an in-depth analysis of SSE. By construction, SSE contains information about both short interest and stock mispricing and thus differs from the level of aggregate short selling (SSL). While both SSE and SSL reveal aggregate demand for short selling, SSL does not guarantee that mispricing will be corrected immediately. In contrast, high SSE reflects active arbitrage activity on the right stocks, following which mispricing should get corrected quickly. More importantly, we argue conceptually and confirm empirically that SSE has the advantage of reducing noises in short selling. In practice, not all short sales are motivated by absolute overpricing. Some may reflect changes in the supply of lendable shares. Others may reflect hedging positions related to convertible bonds, options, or ETFs. Treating all short interests as signals of stock overpricing would consequently introduce positive noises that contaminate SSL. Yet, as long as such noises are uncorrelated with mispricing scores across stocks, they will not affect SSE. We show empirically that SSE is less correlated with aggregate institutional ownership that proxies for the supply side of short selling. After controlling for institutional ownership in the cross-section, SSE continues to exhibit significant predictive ability for stock market returns. This evidence suggests that SSE captures the amount of aggregate short selling capital devoted to overpricing better than SSL does.

Furthermore, we gain insights from additional analyses. We examine how the prediction varies with market conditions and information environments to infer the source of SSE's predictive power. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) argue that information processing is especially valuable in recessions when aggregate payoff shocks are more volatile. Consistent with their argument, we find that the predictive power of SSE is particularly strong in recessions and high-volatility periods. In addition, the predictive power is stronger in the periods with less public information than the periods with more public information. These findings complement existing research about the cross-section of stocks (e.g., Cohen, Diether, and Malloy, 2007; Boehmer, Jones, and Zhang, 2008; Engelberg, Reed, and Ringgenberg, 2012) and provide new evidence that short sellers are informed in aggregate. We provide further evidence of SSE's predictive power for stock market returns based on daily data.

Finally, we relate short selling efficiency to stock market efficiency by examining the relation between SSE and the performance of the capital asset pricing model (CAPM). Following periods with low SSE, a significant upward slope of the security market line (i.e., the relation between market beta and stock return) emerges, supporting the prediction of the CAPM. Based on ten decile portfolios formed on market beta, the security market line has a slope of 0.89 (t-value = 11.09). In contrast, following periods with high SSE, the security market line is downward sloping. Recent research finds that the CAPM performs well in certain market conditions related to macroeconomic announcement (Savor and Wilson, 2014), investor sentiment (Antoniou, Doukas, and Subrahmanyam, 2016), and margin requirement (Jylha, 2018). In this paper, we provide novel evidence on how short selling efficiency relates to the performance of the CAPM.

Our paper makes several contributions to the literature. First, our paper adds to the large literature of how short sales predict stock returns. Prior research focuses on the cross-sectional predictability of short selling and its constraints, including Nagel (2005), Cohen, Diether, and Malloy (2007), Boehmer, Jones, and Zhang (2008), Diether, Lee, and Werner (2009a), Engelberg, Reed, and Ringgenberg (2012), Hanson and Sunderam (2014), and Drechsler and Drechsler (2016).

In particular, Nagel (2005) and Hanson and Sunderam (2014) examine the relation between short sales and return anomalies. Our paper complements the existing research by investigating the predictive power of short selling efficiency for *aggregate* stock returns.

Second, our paper is closely related to Rapach, Ringgenberg, and Zhou (2016), who show that the level of short interest predicts the equity premium. The authors assert that "short interest is arguably *the* strongest predictor of the equity market premium identified to date" (p. 46). Combining mispricing information (i.e., stock anomalies) with short interest, our predictor of short selling efficiency contains distinctive signals and sheds new light on how short sellers influence stock markets. Importantly, our study is motivated by the fundamental economic insight that how scarce resources for short selling are allocated across different stocks should impact the overall market efficiency. To the best of our knowledge, our paper is the first to link the disposition of short selling to aggregate stock price movement.

Finally, our study contributes to the literature on market return predictability. Given the importance of the equity market premium in practice, there has been decades-long research about this topic (see, e.g., Goyal and Welch (2008) and Rapach and Zhou (2013) for excellent surveys).[2] Numerous studies have examined the predictive power of variables constructed from firm fundamentals (e.g., payout ratio and book-to-market ratio) and macroeconomic conditions (e.g., bond yield spread and investor sentiment). Our innovation is to show that the efficiency of arbitrageurs such as short sellers contains significant predictive signals for stock market returns.

The paper proceeds as follows. Section 2 describes the construction of the SSE measure. Section 3 summarizes the data of SSE along with other return predictors. Section 4 presents the main results and robustness tests on SSE's predictive power for market returns. In Section 5, we digest the results by analyzing SSE in greater detail. Section 6 provides additional analyses. Finally, Section 7 concludes. A stylized model is included in the Appendix to illustrate the mechanism underlying the return predictability.

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[2] For recent studies on forecasting the equity premium, see, for example, Boudoukh, Richardson, and Whitelaw (2008), Campbell and Thompson (2008), Cochrane (2008), Goyal and Welch (2008), Lettau and van Nieuwerburgh (2008), Pastor and Stambaugh (2009), Rapach, Strauss, and Zhou (2010), Dangl and Halling (2012), Huang, Jiang, Tu, and Zhou (2015), Rapach, Ringgenberg, and Zhou (2016), Da, Huang, and Yun (2017), Chen, Eaton, and Paye (2018), among others. See Rapach and Zhou (2013) for a survey of the earlier research in this literature.

2. Measuring short selling efficiency (SSE)

In our setting, short selling is efficient if more short sales occur to overpriced stocks relative to the other stocks (especially undervalued stocks). We propose an empirical measure of the efficiency based on the following cross-sectional regression:

$$ASI_{i,t} = a_t + b_t\, MISP_{i,t} + e_{i,t}, \qquad (1)$$

where ASI is the abnormal short interest. For each stock in our sample, we calculate its monthly short interest as the number of shares sold short in the month divided by the total number of shares outstanding. Similar to Chen, Da, and Huang (2019), we define abnormal short interest for each stock in each month as the value of short interest in the current month minus the average short interest over the past 12 months. MISP measures stock mispricing with a large (small) value indicating overpricing (underpricing). For our empirical analysis, we adopt the comprehensive mispricing percentile ranking measure of Stambaugh, Yu, and Yuan (2015). To ease interpretation of the regression coefficients, MISP is demeaned cross-sectionally. In each cross-section, MISP is therefore uniformly distributed across stocks and ranges from -0.5 for the most underpriced stocks to 0.5 for the most overpriced stocks.

The regression coefficient of interest is the slope coefficient b_t, capturing short selling efficiency in month t. In the regression, the slope coefficient measures the covariance between ASI and MISP (scaled by the variance of MISP which is a constant).[3] All else being equal, a large positive value of *b* indicates that short selling is executed on the right stocks, i.e., overpriced stocks. Essentially, SSE can be viewed as short interest put on overpriced stocks minus short interest put on underpriced stocks, since the regressor MISP is demeaned. (We construct an alternative measure of SSE based on this intuition later.) We therefore posit that combining information from

[3] Among the 11 anomaly variables underlying the MISP constructed for month t, except for the distress variable that potentially uses information in month t, the other 10 variables are all constructed using information prior to month t. Since short interest is measured at the middle point of month t, SSE mostly reflects short sellers' response to mispricing. We also compute a version of SSE using one-month lagged value of MISP in Equation (1), and the inference remains unchanged. This is not surprising given that MISP is highly persistent at the stock level.

both the magnitude and the location of short interest, SSE serves as a predictor for aggregate stock returns.

In addition, since MISP has zero mean, the intercept a_t is the mean level of abnormal short interest in the month (i.e., the equal-weighted average of abnormal short interest across individual stocks), thus capturing aggregate short selling level (SSL) in the stock market. As shown in Rapach, Ringgenberg, and Zhou (2016), aggregate short interest is significantly related to overall mispricing in the market as well.

However, SSE (coefficient b) differs from SSL (coefficient a) in important aspects. While SSL does not distinguish between different stocks, SSE takes a large value when short selling is well aligned with overpricing. In practice, not all short sales are for arbitrage purposes, and short selling can sometimes even occur to undervalued stocks. For example, investors may sell short a stock simply to hedge their positions in other stocks, bonds, and options. Short selling unrelated to mispricing introduces positive noises to SSL as a measure of aggregate overpricing. Such noises can also change over time driven by the supply of lendable shares and regulations on short selling. The noises contain little predictive information but reduce the power to identify a predictive relation. Importantly, as long as such noises are uncorrelated with the mispricing scores, they will show up similarly in overpriced and underpriced stocks. The emphasis of SSE on the difference between overpriced and underpriced stocks therefore mitigates the impact of noises in short selling across all stocks. Put differently, although the noises contaminate the information content of aggregate short interest, SSE has the noises cancelled out between overpriced and underpriced stocks. Using a stylized model, we provide further discussion about SSE’s predictive power as well as the contrast between SSE and SSL in the Appendix. Intuitively, a higher degree of market overvaluation means that more stocks are overpriced in the cross-section. Since short sellers are informed, they correctly devote more capital to the more overpriced stocks, consistent with Hanson and Sunderam (2014). Both forces work together to increase the covariance between ASI and MISP, or SSE, explaining why a high SSE signals market overpricing today and predicts lower aggregate returns in the future.

3. Data

3.1. The SSE measure

The first element to measure SSE is abnormal short interest at the stock level. We employ short interest data from the Compustat Short Interest File, which reports monthly short interest for stocks listed on the NYSE, AMEX, and NASDAQ. Since the Compustat Short Interest File only started the coverage of NASDAQ stocks from 2003, we follow the literature to supplement our sample with short interest data on NASDAQ prior to 2003 obtained directly from the exchange. The data have been used in several previous studies to examine the impact of short interest on stock prices (e.g., Asquith, Pathak, and Ritter, 2005; Hanson and Sunderam, 2014; Chen, Da, and Huang, 2019). Based on the data, we calculate the abnormal short interest for each stock each month from January 1974 to December 2017. In particular, we use the short interest as of the middle of the month to ensure that it is in investors' information set when forming expectations of next-month market returns.

The second element required for computing SSE is a stock-level measure of mispricing. We adopt the mispricing measure of Stambaugh, Yu, and Yuan (2015), constructed from a combination of 11 well-known stock return anomalies.[4] The original measure is a composite rank between 1 and 100 across stocks based on various stock characteristics, with a higher rank indicating overpricing and a lower rank indicating underpricing. To suit our analysis, we rescale and demean the rank measure each month so the most overvalued (undervalued) stock in the cross-section has a score of 0.5 (-0.5). The resulting variable is MISP used in regression (1). Each month, the intercept and slope coefficient of the regression correspond to the short selling level (SSL) and short selling efficiency (SSE) for that month, respectively.[5]

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[4] These stock return anomalies include financial distress, o-score bankruptcy probability, net stock issues, composite equity issues, total accruals, net operating assets, momentum, gross profitability, asset growth, return on assets, and investment to assets.

[5] Note that although SSL shares the similar economic meaning with the short interest index (SII) proposed in Rapach, Ringgenberg, and Zhou (2016), there exist substantive differences in the construction of the two variables. When constructing the SII, Rapach, Ringgenberg, and Zhou (2016, p. 47) first calculate the log of the equal-weighted mean of short interest (scaled by shares outstanding) across stocks in each month, then detrend the short interest series, and finally standardize the detrended series to create the short interest index, SII. Their procedure differs from the way SSL is measured based on abnormal short interest. In addition, the SII is constructed from a sample of common stocks,

In our baseline analysis, we require stocks to have non-missing values of ASI and MISP to be included in regression (1). In addition, we exclude micro-cap stocks and stocks whose prices are less than five dollars. As robustness checks, we later include micro-cap stocks in the analysis in Section 4.

As documented by Rapach, Ringgenberg, and Zhou (2016), there has been an upward trend in short selling since the 1970s, perhaps reflecting the rise of hedge funds as the main group of short sellers in the U.S. stock market.[6] As a result, the monthly time-series of both SSE and SSL display upward trends. Following Rapach, Ringgenberg, and Zhou (2016), we remove the time trend in both SSE and SSL and standardize both variables to mitigate the effect of secular trend on our results. Our inference remains unchanged if we do not detrend the predictors (see Section 4 for details).

Panel A of Table 1 summarizes the SSE measure over the sample period from January 1974 to December 2017. In this paper, our focus is on the time-series properties of SSE. Indeed, we observe substantial variation of SSE over time, suggesting that short sellers do not always allocate trades to the right stocks. Meanwhile, the series of SSE exhibit a first-order autocorrelation of 0.84.

[Insert Table 1 about here.]

Figure 1 delivers a similar message by plotting the time series of SSE during the sample period. A few large values of SSE occur near some famous market downturns such as the tech bubble burst, the subprime mortgage crisis, and the 2008-2009 financial crisis. Such a pattern could be explained by the fact that it is easier to locate overpriced stocks at these episodes. As shown in Figure 1, SSE departs from SSL to a substantive extent over time, suggesting that these variables

American depositary receipts, exchange traded funds, and real estate investment trusts. In our paper, SSL is obtained from common stocks only, because the mispricing score used to measure both SSE and SSL is compiled based on stock anomalies and hence available for stocks only.

[6] In recent years, over 80% of short selling has been performed by hedge funds (see, e.g., Ben-David, Franzoni, and Moussawi, 2012; Chen, Da, and Huang, 2019).

capture different information. For example, while the level of short selling dropped substantially during the 2008-2009 financial crisis, SSE did not seem to decline as much during the same period, suggesting that constrained short sellers can still be efficient in allocating their capital across stocks. In addition, SSE appears to be more volatile than SSL during the first half of the sample period.

[Insert Figure 1 about here.]

3.2. Other return predictors

Panel A of Table 1 also reports summary statistics for other return predictors that are used for comparison purposes. Specifically, we collect data for the following return predictors, including both classic predictors in the literature and recently proposed predictors. The data sources are Compustat, the Fed Reserve Bank of St. Louis, and the websites of several researchers.[7] All the variables except price multiples are multiplied by 100 in the table.

1. Short selling level (SSL): detrended equal-weighted average abnormal short interest, similar to the short interest index used in Rapach, Ringgenberg, and Zhou (2016).
2. Investor sentiment (Sent): aggregate sentiment measure of Baker and Wurgler (2006), constructed as a composite of six variables, namely equity new issues, closed-end fund premium, NYSE share turnover, the number and average first-day returns of IPOs, and the dividend premium.
3. Price-earnings ratio (PE): log value of the ratio of stock price to the moving average earnings per share over the recent 10 years, as in Campbell and Shiller (1988a).
4. Price-dividend ratio (PD): log value of the ratio of stock price to dividend payment, as in Ball (1978), Campbell and Shiller (1988a, 1988b), among others.

[7] We are grateful to Zhuo Chen, Amit Goyal, Zhiguo He, Bryan Kelly, Asaf Manela, Robert Shiller, Robert Stambaugh, Ivo Welch, Jeffrey Wurgler, Jianfeng Yu, and Guofu Zhou for making a large amount of data used in their research available to us.

5. Credit spread (CS): the difference in bond yield between BAA- and AAA-rated corporate bonds, as in Keim and Stambaugh (1986) and Fama and French (1989).
6. Term spread (TS): the difference in bond yield between long-term government bonds and the three-month T-bill, as in Campbell (1987) and Fama and French (1989).
7. Three-month T-bill rate (TB3): three-month T-bill rate, as in Campbell (1987) and Hodrick (1992).
8. Funding liquidity spread (FLS): aggregate funding liquidity measured by the return spread between stocks with high margins and stocks with low margins, proposed by Chen and Lu (2019).
9. Capital ratio (CAPR): aggregate funding liquidity measured by the equity capital ratio of major financial intermediaries, proposed by He, Kelly, and Manela (2017).
10. Long-term bond return (LTR): return on long-term government bonds, as in Goyal and Welch (2008).
11. Return volatility (RVOL): Standard deviation of excess stock market returns over the past 12 months, as in Goyal and Welch (2008).

The summary statistics of these predictive variables are consistent with the literature. Many of the variables exhibit substantial first-order autocorrelation. In fact, all of them, except the funding liquidity spread and long-term bond return, have the autocorrelation coefficients greater than 0.90.

Panel B of Table 1 presents the correlations between SSE and the other return predictors. Not surprisingly, SSE and the short selling level (SSL) are positively correlated, with a correlation coefficient of 0.60, as the existence of overpricing should motivate arbitrageurs to short more stocks, especially the most overpriced ones. Meanwhile, SSE bears relatively low correlations with the 10 other predictors, suggesting that SSE contains different information from the predictors constructed from firm fundamentals and macroeconomic conditions.

4. Main results

In this section, we first evaluate the in-sample forecasting power of SSE for stock market returns over different forecasting horizons and compare it with the other return predictors. We then assess the out-of-sample predictive ability of SSE. Finally, we show the robustness of our results to various sensitivity checks.

4.1. In-sample predictability

We start by examining how well SSE performs using the following univariate predictive regression, in which the dependent variable is the subsequent excess market returns over various forecasting horizons.

$$r_{t:t+s} = \alpha + \beta x_t + \varepsilon_{t:t+s}, \quad (2)$$

where $r_{t:t+s} = (r_{t+1} + \cdots + r_{t+s})/s$, i.e., the average monthly excess market return over the forecasting horizon s. The excess market return is measured by the CRSP value-weighted aggregate stock index return in excess of one-month T-bill return for each month. Our inference is robust to using alternative measures of the excess market return, such as the one based on the S&P 500 index. The forecasting horizon s varies from one, three, six, to 12 months. x is the return predictor at a month frequency. For comparison purposes, we perform the same analysis for the other predictors. The reported regression coefficients are multiplied by 100. Following Rapach, Ringgenberg, and Zhou (2016), we report t-values based on the Newey-West (1987) standard errors with eight lags, and we verify that our inference remains unchanged using the Hodrick (1992) t-value.

Table 2 presents the regression results. For the main predictor of interest SSE, the regression coefficient with a one-month forecasting horizon is -0.61 (t-value = -3.50), implying that a one-standard deviation increase in SSE would be followed by a decrease in the excess market return by 0.61% in the next month. The adjusted R^2 is as large as 1.64%. Moving to longer forecasting horizons, SSE still predicts future excess market returns in an economically and statistically significant fashion. For example, at the three-month horizon, the regression coefficient is -0.64 (t-value = -3.27), similar to that at the one-month horizon, suggesting that SSE has similar predictive power for the first-, second-, and third-month market return going forward. At the 12-month horizon, the regression coefficient is -0.40 (t-value = -3.69) with an adjusted R^2 8.49%. The finding of increased R^2 with longer forecasting horizons is consistent with the existing literature (e.g., Fama and French, 1988; Boudoukh, Richardson, and Whitelaw, 2008). In addition, the long-horizon result suggests that the forecasting power is less likely to arise from temporary price pressure but more likely from market-wide information.

[Insert Table 2 about here.]

The predictive power of SSE compares favorably with the other return predictors proposed in the literature. Consistent with Rapach, Ringgenberg, and Zhou (2016), we find that a high level of abnormal short interest precedes low excess market returns. The regression coefficients for SSL are -0.22, -0.43, -0.56 and -0.45 at the one-, three-, six- and 12-month horizons, respectively, compared with the coefficients for SSE at -0.61, -0.64, -0.62, and -0.40 over the same horizons. Since both predictors are standardized, their regression coefficients can be compared directly. Thus, SSE performs at least as well as SSL and possesses strong predictive power at all the forecasting horizons.

The other predictors, such as financial ratios and market conditions, generally show correct signs in forecasting aggregate stock returns, but they are not always statistically significant especially over shorter horizons. Consistent with Rapach, Ringgenberg, and Zhou (2016), long-term bond return and return volatility exhibit significant predictive power. In addition, as the forecasting horizon extends to a longer period, some predictors exhibit better predictive ability judging by t-value and adjusted R^2. For example, the price-dividend ratio predicts excess market returns with a coefficient of -0.02 (t-value = -1.87) and an adjusted R^2 of 4.58% at the 12-month horizon, compared with a coefficient of -0.01 (t-value = -1.10) and an adjusted R^2 of 0.08% at the one-month horizon.

To test whether SSE has distinct forecasting power for the equity premium, we perform bivariate predictive regressions that control for the other predictors, one at each time. Table 3 reports the findings with each panel corresponding to a different forecasting horizon. Panel A shows that SSE still forecasts the equity premium well in the presence of the other predictors. For example, when we include both SSE and SSL in the one-month forecasting regression, SSE has a regression coefficient of -0.75 (t-value = -3.03), compared with the coefficient of 0.22 (t-value = 0.90) on SSL. Thus, SSE continues to exhibit significant predict power for stock market returns after controlling for aggregate short interest. Similarly, controlling for the other predictors does not subsume the forecasting power of SSE. We obtain the same inference at longer forecasting horizons, as shown in Panels B through D.

Interestingly, at the 12-month horizon, SSL exhibits stronger predictive power than SSE judging by larger regression coefficient and greater t-value in absolute term. In addition, the adjusted R^2 from the bivariate regression including both SSE and SSL, 12.16%, is higher than that from the univariate regression for SSE at 8.49%. This finding suggests that while SSE predicts market returns well at short horizons, SSL carries information about the stock market over long horizons. This difference makes sense. SSE captures active trading on mispriced stocks and thus mispricing gets corrected more quickly. In contrast, SSL reflects the level of overpricing but does not guarantee that mispricing will be corrected immediately. As a result, we observe the outperformance of SSE in predicting stock market returns over short horizons and the relative strength of SSL over long horizons.

[Insert Table 3 about here.]

Finally, we perform multivariate regressions by including the short interest index (SII) of Rapach, Ringgenberg, and Zhou (2016), short selling level (SSL), 10 other return predictors, and 11 aggregate (as average value across individual stocks) stock anomalies underlying the mispricing measure of Stambaugh, Yu and Yuan (2015) in the predictive regressions. For example, after controlling for the SII and the 10 other return predictors, the coefficients for SSE are -0.48 (*t*-value = -2.34), -0.45 (*t*-value = -2.16), -0.43 (*t*-value = -2.80), and -0.16 (*t*-value = -1.65) at the one-, three-, six-, and 12-month horizons, respectively. Meanwhile, SII exhibits strong predictive power at the longer horizon of 12 months, suggesting that SII and SSE complement each other in forecasting market returns. Including the aggregate stock anomalies in multivariate regressions produces similar results about the predictive power of SSE. In addition, except for gross profitability, asset growth, and momentum, the aggregate anomaly variables generally have insignificant power to predict market returns, consistent with the findings in Engelberg, McLean, Pontiff, and Ringgenberg (2020).

[Insert Table 4 about here.]

In sum, we show evidence that SSE contains significant predictive signals for the equity premium. Its return predictive power is over and above that of aggregate short selling, other return predictors, and stock anomalies. We also find that SSE predicts stock market returns particularly well over short horizons.

4.2. Out-of-sample predictability

Recent research on market return predictability, following Goyal and Welch (2008), emphasizes the importance of out-of-sample forecasting performance to help validate in-sample performance. In this subsection, we evaluate the predictive power of SSE for aggregate stock returns based on out-of-sample tests. Following the literature, we test whether SSE can outperform the historical average of stock market returns in forecasting the equity premium.

We first run the following time-series regression using a subsample with information up to month t:

$$r_t = \alpha + \beta x_{t-1} + \varepsilon_t, \tag{3}$$

where r_t is excess market return for month t, and x_{t-1} is one-month lagged value of the predictor. Then, based on the regression coefficient estimates only using information up to month t, we compute the forecast of the equity premium for month t +1.

Next, we either expand the subsample by one additional month each time (expanding approach) or use a fixed rolling window of 10-year data (rolling approach), and thereby generate the sequence of equity premium forecasts, $\hat{r}_{t+1}$, $\hat{r}_{t+2}$, …, $\hat{r}_T$. Following Campbell and Thompson (2008) and Goyal and Welch (2008), the out-of-sample R^2 compares the mean-squared errors obtained from the predictor with those from the historical average. That is,

$$R^2 = 1 - \frac{\sum_{\tau=t+1}^{T}(r_\tau - \hat{r}_\tau)^2}{\sum_{\tau=t+1}^{T}(r_\tau - \bar{r}_\tau)^2}\ , \tag{4}$$

where $\bar{r}_\tau$ is the historical average of excess market returns up to month τ - 1, and T is the total number of months over the entire sample period. A positive out-of-sample R^2 indicates outperformance of the predictor relative to the historical average. We compute p-values for the test statistic based on the Clark and West (2007) method.

Similar to Campbell (1991), we remove the time trend in SSE and SSL stochastically using information up to month t. Specifically, we use the data from January 1974 to December 1975 as the first subsample to remove the time trend. We then standardize the residuals of the time-trend regression and retain the last observation to be matched with stock market return over the next month. We extend the subsample by one month at a time. This stochastic detrending procedure ensures real-time forecasting. In addition, we winsorize SSE and SSL at 1% and 99% only using data up to month t. For both the expanding and the rolling approaches, our initial regression uses stock market return data of 10 years (January 1976–December 1985) and thus the out-of-sample prediction (i.e., month t + 1 in Equation (4)) starts in January 1986.

Following Campbell and Thompson (2008), we consider three cases of economic restrictions. The first case imposes no restriction. The second case imposes the coefficient sign restriction, which sets an equity premium forecast to the historical average when the coefficient sign is incorrect (e.g., a positive coefficient for SSE). The third case imposes the premium sign restriction, which sets an equity premium forecast to zero when the forecast value is negative.

Table 5 presents the results of out-of-sample performance. Based on both the expanding approach and the rolling approach, we find evidence that SSE performs significantly better than the historical average in forecasting the equity premium across all three cases. With the expanding sample, the out-of-sample R^2 for SSE is positive and significant in all of the three cases, ranging from 0.99% (p-value = 0.04) to 1.41% (p-value = 0.02). Similarly, using the 10-year rolling window, we observe out-of-sample R^2 varying from 1.03% (p-value = 0.02) to 1.67% (p-value = 0.02).

[Insert Table 5 about here.]

Meanwhile, SSL also exhibits significant out-of-sample forecasting power, consistent with the result of Rapach, Ringgenberg, and Zhou (2016). In contrast, the out-of-sample performance of the other predictors is not strong over our sample period 1974 to 2017, except that sentiment and long-term bond return show significant outperformance over the historical average in certain cases. Such results about those other predictors largely echo the finding of Goyal and Welch (2008) that many predictors do not outperform the historical average in out-of-sample tests. Nonetheless, none of the predictors significantly underperforms the historical average judging by their p-values.

To summarize, the out-of-sample tests show that SSE outperforms the historical average in predicting the equity premium. This suggests that SSE, combining information of short selling and stock mispricing, can potentially guide asset-allocation decisions in real time. Therefore, both in-sample and out-of-sample results strongly support the view that the efficiency of short selling contains economically and statistically significant signals about future stock market returns.

4.3. Robustness tests

In this subsection, we check the robustness of our results from seven different aspects. First, we investigate the predictive ability of un-detrended SSE. Second, we examine an alternative measure of SSE based on the spread in abnormal short interest between overpriced and underpriced stocks. Third, we include micro-cap stocks in the sample so that the resulting SSE covers nearly all public firms. Fourth, we include lagged values of stock market return, market volatility, and trading volume as control variables when computing SSE. Fifth, we study the impact of the 2008-2009 financial crisis and the short-sale ban. Sixth, we examine the out-of-sample predictability over horizons longer than one month. Finally, we perform a bootstrap analysis to address the concern that SSE may include measurement error.

4.3.1. Un-detrended SSE

Both SSE and SSL exhibit a time trend, reflecting a steady rise of short selling activity. We detrend these predictors in the analyses above to avoid the potential impact of time trend on our inference. We now examine the predictive power of the un-detrended SSE for two purposes. First, it checks the robustness of SSE as a market return predictor. Second, we can evaluate the effect of time trend on our inference.

Specification (1) of Panel A in Table 6 presents the in-sample predictive power of the un-detrended SSE. We find that SSE continues to exhibit significant forecasting ability for stock market returns. In the test, the coefficient on SSE from the univariate predictive regression is -0.47 (t-value = -2.21) at the one-month horizon, -0.48 (t-value = -2.33) at the three-month horizon, -0.47 (t-value = -2.57) at the six-month horizon, and -0.31 (t-value = -2.20) at the 12-month horizon. While the magnitude is slightly weaker than that from the detrended series presented in Table 2, the result nonetheless suggests that the un-detrended SSE remains to be an effective predictor of the equity market premium.

Specification (1) of Panel B in Table 6 reports the out-of-sample test result. As before, we use two alternative approaches—expanding the sample and a 10-year rolling window. For each approach, we consider the three different cases of economic restrictions. From both approaches, the un-detrended SSE exhibits a positive out-of-sample R^2 across the three cases, indicating that the predictor outperforms the historical average in forecasting stock market returns.

[Insert Table 6 about here.]

In sum, our inference is robust to whether or not we detrend SSE. Nonetheless, the detrended SSE exhibits slightly stronger predictive power than the raw SSE. As discussed before, considering the secular trend of SSE over time, we prefer to follow the literature (e.g., Rapach, Ringgenberg, and Zhou, 2016) to remove time trend in the main analysis.

4.3.2. Alternative measure of SSE: The O-U spread

Our measure of SSE comes from the slope coefficient of the regression of abnormal short interest on the overpricing score of Stambaugh, Yu, and Yuan (2015) across stocks. A large value of SSE shows high comovement between short sales and overpricing in the cross-section. As an alternative measure, we use the spread in abnormal short interest between most overpriced stocks and most underpriced stocks. Specifically, we use O (U) to denote the average abnormal short interest of stocks in the top (bottom) decile portfolio ranked by the mispricing score. We then construct the O-U spread as the alternative measure of SSE. That is, we assign a weight of +1 (-1) to the top (bottom) decile of mispriced stocks in each month, and a weight of 0 to other stocks. The stylized model in the Appendix confirms that the O-U spread also captures market-level overpricing as SSE does. The O-U spread has the benefit of simplicity without using regression which assumes a linear relation between ASI and MISP. As a trade-off, it drops information in the remaining eight decile portfolios.

We present the in-sample results from the O-U spread in specification (2) of Panel A in Table 6. As can be seen, the O-U spread significantly and negatively predicts stock market returns over all the horizons. For example, the coefficient on the O-U spread from the univariate predictive regression is -0.54 (t-value = -3.48) with an R^2 of 1.25% at the one-month forecasting horizon.

Furthermore, as presented in specification (2) of Panel B in Table 6, the out-of-sample result shows that the O-U spread predicts market returns better than the historical average based on both the expanding and rolling approaches.

4.3.3. Including micro-cap stocks

The sample used in our main analyses excludes micro-cap stocks. To evaluate whether this subset of stocks could affect our inference, we augment the original sample by adding back such stocks and thus use nearly the entire stock market to form SSE. The rationale for the test is that short sales are perhaps heavily placed on extremely small stocks due to severe information asymmetry. On the other hand, given their small firm size, these stocks do not have a large representation in the value-weighted market returns, and thus their presence seems unlikely to alter our inference.

Specification (3) of Panel A in Table 6 repeats the univariate regression analysis for the augmented sample. SSE continues to exhibit significant forecasting power at all forecasting horizons examined. Specifically, the coefficient on SSE is -0.55 (t-value = -3.40) at the one-month horizon, -0.55 (t-value = -3.41) at the three-month horizon, -0.43 (t-value = -2.97) at the six-month horizon, and -0.27 (t-value = -2.34) at the 12-month horizon. These numbers are close to, though somewhat smaller than, those obtained from the main sample excluding micro-cap stocks, suggesting that the effect of adding such stocks to the analysis is minor.

In specification (3) of Panel B in Table 6, we report the out-of-sample test result for SSE computed based on the augmented sample. As can be seen, the reconstructed SSE outperforms the historical average in forecasting future aggregate stock returns. From the expanding approach, SSE's out-of-sample R^2 is between 0.80% and 1.12% with p-values of 0.05 or lower in all of the three cases. The result from the rolling approach delivers a similar message. Our findings are therefore robust to the inclusion of micro-cap stocks in the sample.

4.3.4. Controlling for other drivers of short selling

The multivariate predictive regressions performed in Table 4 include other return predictors proposed in the literature. For robustness, we now include lagged values of volatility, trading volume, and stock return as control variables in Equation (1) when computing SSE and then perform the predictive regression. Diether, Lee, and Werner (2009a) show that short sellers react to these variables using a daily sample. As such, this version of SSE measures short sellers' response to MISP above and beyond other previously documented drivers of short selling.

Specification (4) of Panel A in Table 6 presents results from the predictive regressions using the version of SSE that is estimated with these control variables. The coefficient of market returns on this alternative SSE is -0.41 (t-value = -2.45), -0.40 (t-value = -2.41), -0.39 (t-value = -2.95), and -0.26 (t-value = -2.92) at the one-, three-, six-, and 12-month horizons, respectively. These values are slightly lower than those in the baseline analysis, indicating that the control variables contain overlapping information with MISP. Nonetheless, SSE survives the controls and continues to show significant forecasting power. In un-tabulated results, we find the average coefficient of ASI on lagged volatility is 0.0466 (t-value = 8.78), on lagged trading volume is 0.0024 (t-value = 21.35), and on lagged stock return is -0.0001 (t-value = -0.14).

In specification (4) of Panel B in Table 6, we perform the out-of-sample test for this version of SSE. Based on both expanding and rolling approaches, the results are in favor of significant out-of-sample predictability. Taken together, the predictive power of SSE is robust to controlling for volatility, trading volume, and past return when we regress ASI on MISP to estimate SSE.

4.3.5. Short-sale ban and financial crisis

Our sample period covers the 2008-2009 financial crisis. Amid the market crash, SEC temporarily banned most short sales on almost 1,000 financial stocks in September 2008 (Boehmer, Jones, and Zhang, 2013). Thus, one natural concern is: could the short-sale ban and more broadly the financial crisis drive SSE's return predictability?

We first verify that, while financial stocks experience a sharper decrease in short interest in September 2008 (relative to other stocks), the short interest for such stocks is not zero even during the ban, partly because option market makers are still allowed to short these stocks to hedge their positions. In this case, investors can still "short" the stocks by trading options (e.g., writing calls or buying puts). Accordingly, option market makers short the underlying stocks to hedge, thus effectively expressing investors' short interest in the stock market, consistent with the evidence in Battalio and Schultz (2006) and Hu (2014). We also find a higher SSE among financial stocks than that among other stocks during the short-sale ban, suggesting that constrained short selling can be particularly informative.

To ensure that SSE's return predictability is not driven by the financial crisis, we exclude July 2008–January 2009 (the period of stock market crash which also covers the short-sale ban) from our analysis in specification (5) of Panel A in Table 6. SSE remains highly significant in predicting future market returns. The results are similar if we exclude the period 2008–2009 entirely.

4.3.6. Out-of-sample predictability at longer horizons

So far, our analyses of out-of-sample prediction focus on one-month-ahead stock market returns. Here, we evaluate the out-of-sample predictive power at longer horizons of three, six, and 12 months. To this end, we continue to use the detrended SSE and perform out-of-sample tests with the average monthly excess market return over each forecasting horizon as the left-hand-variable in regression (3). As before, we consider three cases regarding economic restrictions.

Panel C of Table 6 presents the results. Based on both the expanding and the rolling approaches, we find that SSE significantly outperforms the historical average in forecasting the equity premium at these long horizons. This finding holds across all three cases. For example, in the expanding approach with no economic restriction, the out-of-sample R^2 for SSE is 1.53% (p-value = 0.06) at the three-month horizon and 5.26% (p-value = 0.01) at the six-month horizon. Imposing the restriction about the sign of the regression coefficient enhances the out-of-sample forecasting power. At the 12-month horizon, the out-of-sample R^2 for SSE somewhat weakens but continues to be statistically significant for most cases. Overall, the out-of-sample tests at longer forecasting horizons show that SSE outperforms the historical average of market returns in predicting the equity premium up to one year.

4.3.7. Bootstrap analysis

Finally, to account for measurement error in estimating SSE, we conduct a bootstrap exercise in which we resample both the cross-section and the time-series. In a bootstrap iteration, we resample stocks with replacement in the cross-section for each month and estimate SSE for the month. The time-series of SSE is then detrended and standardized. We then draw blocks of three consecutive observations from the time-series of SSE and market returns. We use a block size of three because the BIC of an autoregressive process for the original SSE suggests two lags. Next, we run the predictive regression and record the coefficient on SSE. Finally, the iteration is repeated 1,000 times. Panel D of Table 6 reports the average coefficient and adjusted R^2 across all iterations. The regression coefficients on SSE are similar to those reported in Table 2. The p-values are close to zero for all the forecasting horizons, indicating significant predictive power. Therefore, the results from the bootstrap analysis confirm that SSE contains predictive information about future market returns, and such predictability cannot be attributed to measurement error.

5. Digesting the results

Why does SSE contain superior predictive signals relative to SSL? In Section 2 and the stylized model in the Appendix, we argue that SSE has the advantage of reducing the impact of noises in short selling. Such noises arise from short selling unrelated to stock overpricing and thus contain no predictive signals for future aggregate returns. Capturing the difference in short selling between overpriced and underpriced stocks, SSE mitigates the effect of noises. We perform formal analyses to evaluate this argument in this section.

5.1. Understanding SSE and SSL

To fix ideas, we focus our discussion here on short selling placed on overpriced stocks and underpriced stocks and omit the other stocks. Given such a focus, our analyses mainly use the O-U spread, i.e., the difference in abnormal short interest (ASI) between overpriced and underpriced stocks, as the measure of short selling efficiency. Similarly, to proxy for aggregate short interest, we use the O+U measure, i.e., the sum of ASI of overpriced stocks and underpriced stocks, as an alternative measure of SSL. We then use O-U and O+U to forecast returns on overpriced and underpriced stocks, separately.

Panel A of Table 7 shows the similarities between O-U and SSE, and also between O+U and SSL. The correlation between O-U and SSE is 0.88, confirming that the two measures share largely overlapped information. Similarly, the correlation between O+U and SSL is as large as 0.97. Meanwhile, the correlations between O-U and SSL, and between O+U and SSE are lower (0.55 and 0.64). These correlations confirm that O-U and O+U are close substitutes of SSE and SSL, respectively.

[Insert Table 7 about here.]

If SSE mitigates the effect of noises that contaminate SSL, we should expect O-U to have better predictive ability than O+U, especially for overpriced stocks. Panel B of Table 7 reports the results from univariate predictive regressions of O+U and O-U for overpriced and underpriced stocks, separately. Here, O-U exhibits favorable predictive power relative to O+U at short horizons. For example, at the one-month forecasting horizon, the regression coefficient on O-U is -0.68 (t-value = -3.20) and the adjusted R^2 is 1.44% for excess returns on the portfolio of overpriced stocks while the coefficient on O+U is -0.40 (t-value = -1.85) and the adjusted R^2 is 0.37% for the same portfolio of overpriced stocks. Meanwhile, at the one-month forecasting horizon, the coefficient on O-U is -0.39 (t-value = -3.00) and the adjusted R^2 is 0.70% for excess returns on the portfolio of underpriced stocks, in comparison to the coefficient on O+U as -0.20 (t-value = -1.49) and the adjusted R^2 of 0.03%.[8, 9] These findings are supportive of our argument that SSE helps reduce the impact of noises in short selling. In addition, similar to the evidence about SSL, the O+U measure exhibits strong forecasting power over longer horizons. Thus, consistent with the results in Section 4, the advantage of SSE (measured by O-U here) over SSL (measured by O+U) concentrates in short forecasting horizons.

The Appendix provides further discussion about the contrast between O+U and O-U in predicting future market returns. Since short sellers are informed about overpricing, they will short more overpriced stocks than underpriced stocks, especially when the overall market itself is overpriced. Therefore, O-U, similar to SSE, recovers information about market overpricing. In contrast to O+U, it is not affected by the noises in short selling. Finally, a low O-U (or SSE) indicates overall market underpricing, explaining why it predicts returns of even the underpriced portfolio.

5.2. Controlling for the supply of short selling

To further digest the main results, we connect SSE to institutional ownership on stocks. Since institutional ownership affects the supply of lendable shares (Asquith, Pathak, and Ritter, 2005; Nagel, 2005), short selling tends to be more pervasive (sparse) when institutional ownership is high (low). Nonetheless, short sales driven by increased institutional ownership (the supply side) are not necessarily placed on overpriced stocks. Hence, short selling unrelated to overpricing (the demand side) introduces common noises. Since such short sales do not reflect overpricing, they should contain no predictive signals for future returns. We test this conjecture below.

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[8] When testing the difference in the regression coefficient on O-U between overpriced and underpriced stocks, we find that O-U's predictive power is stronger for overpriced stocks, especially at shorter horizons. For example, at the one-month forecasting horizon, the coefficient on O-U for overpriced (underpriced) stocks is -0.68 (-0.39), and the t-value for such a difference is -2.15, statistically significant at the 5% level.

[9] We also compare the predictive power of O-U and O+U in bivariate regressions. For both overpriced and underpriced stocks, O-U has better predictive ability than O+U at short horizons, since only the coefficient on O-U is significant. For example, at the one-month forecasting horizon, the coefficient on O-U is -0.70 (t-value = -2.44) while the coefficient on O+U is 0.02 (t-value = 0.08) for overpriced stocks, and the coefficient on O-U is -0.44 (t-value = -2.46) while the coefficient on O+U is 0.07 (t-value = 0.37) for underpriced stocks. Additionally, O+U shows significant predictive ability at the longer horizon of one year.

We first examine the relation between aggregate abnormal institution ownership (AIO) and several measures of short selling, including O (abnormal short interest on overpriced stocks), U (abnormal short interest on underpriced stocks), O+U (proxy for aggregate short interest), and O-U (proxy for short selling efficiency). AIO is the difference in institutional ownership of a stock between the current quarter end and its average in the past four quarters. As shown in Panel A of Table 8, AIO positively correlates with all these measures of short selling, suggesting that large supply of lendable shares contributes to short selling. The correlation of 0.29 between O-U and AIO is lower than the correlation of 0.36 between O+U and AIO. This difference in correlation suggests that short selling efficiency is less related to the supply side than aggregate short interest. To the extent that a large AIO leads to common noises in short interest, short selling efficiency is therefore expected to predict future returns better than aggregate short interest.

[Insert Table 8 about here.]

Next, we check the predictive power of SSE after controlling for AIO. If the predictive power of SSE is subsumed by AIO, it would suggest that the supply side of short selling contains significant predictive signals; otherwise, the forecasting power of SSE mainly arises from the demand side. In the test, we examine the predictive abilities of two components of SSE, namely the predicted SSE from AIO and the residual SSE. To compute the predicted SSE, we first regress stock-level ASI on AIO each quarter and take the fitted value, and then we regress the fitted value on the mispricing score to construct the predicted SSE for each quarter. Similarly, replacing the fitted value with residuals from the cross-sectional regression delivers the residual SSE. Then, we run predictive regressions of future stock market returns on the two components separately. The tests are performed at a quarterly frequency, due to the data availability of institutional ownership.

Panel B of Table 8 reports the results. Over the horizons ranging from one to four quarters, the predicted SSE does not exhibit significant predictive power for future stock market returns, while the residual SSE shows strong forecasting ability. For example, at the one-quarter horizon, the predicted SSE has a regression coefficient -0.11 (t-value = -1.26), while the residual SSE has a regression coefficient of -0.22 (t-value = -2.73).

These results suggest that the predictive ability of SSE is mainly from the demand side rather than the supply side of short selling. Taken collectively, we find evidence that SSE reduces the effect of noises and has stronger forecasting power than aggregate short interest.

6. Additional analyses

In this section, we perform additional analyses to further understand the predictive power of SSE. First, we test the predictive ability of SSE conditional on different market conditions to infer the source of the predictive power. Second, we present evidence based on daily data. Finally, we examine the relation between SSE and performance of the capital asset pricing model (CAPM).

6.1. The source of the predictive power

So far, we have shown significant and robust predictive power of SSE for market returns. Here, we investigate the source of such predictability through examining the pattern of its time variation. We hypothesize that, if SSE captures the information advantage of short sellers, its predictive power should be related to information environments of the stock market. Specifically, SSE should forecast well under the conditions when information acquisition is particularly valuable. To test such hypothesis, we examine three information-related market conditions: recession, market volatility, and volume of public information. In all the tests, to forecast excess market return of month t + 1, we use SSE and the condition variables measured in month t.

We first check whether and how the forecasting power of SSE is related to recessions and market volatility. In a rational model, Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) show that information processing is more valuable during recessions when aggregate payoff shocks are more volatile, and hence fund managers should possess market timing skill in recessions. Empirically, Chen and Liang (2007) find that the ability of hedge funds to time the stock market appears especially strong when the market is bearish and volatile, suggesting the existence of market return predictability during these market states.[10] In addition, Chen, Da, and Huang (2019) find that during the financial crisis when capital constraints are likely binding, the stock anomalies that arbitrageurs choose to actively exploit realize particularly large abnormal returns. For these reasons, we expect SSE to contain strong forecasting signals during recessions and the periods of high market volatility.

Panel A of Table 9 reports the predictive power of SSE in normal versus recession periods. The recession periods are defined based on the NBER recession indicators. Specifically, we test the predictive power for excess market returns over the next month during normal and recession months separately. The results reveal significant predictive ability of SSE in both types of periods rather than concentrated in one of them. However, consistent with the hypothesis, SSE exhibits particularly strong forecasting power during recessions. The coefficient on SSE from a univariate predictive regression is -1.16 (t-value = -2.35) in recessions, compared with -0.43 (t-value = -2.32) in normal times. In other words, the prediction coefficient during recessions appears to be nearly three times as large as that during normal times and close to twice as large as the coefficient from the entire sample (-0.61 as shown in Table 2). A test for the difference in the regression coefficient between recessions and normal times yields a p-value of 0.08, indicating statistical significance at the 10% level.[11] Moreover, the adjusted R^2 of the predictive regression is 3.37% during recessions versus 0.78% during normal times.

[Insert Table 9 about here.]

In Panel B of Table 9, we present the predictability conditional on market volatility proxied by the VIX index. SSE shows much stronger forecasting power in volatile periods. For example, at the one-month horizon, the coefficient on SSE from a univariate predictive regression is -1.15

[10] Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) find that mutual fund managers have market timing skill during recessions. Unlike hedge funds that constitute the majority of short sellers, however, mutual funds generally do not hold short positions in stocks (e.g., Almazan, Brown, Carlson, and Chapman, 2004).

[11] Note that such a test is based on regression coefficients obtained from subperiods that have smaller numbers of observations than the entire sample period, which may limit statistical power of the test.

(t-value = -2.49) during high volatility periods when VIX exceeds the time-series median, in contrast to -0.32 (t-value = -1.97) during low volatility periods when VIX falls below its median. The test for the difference in the regression coefficient between high and low VIX periods delivers a p-value of 0.05, indicating statistically significance at the 5% level. Meanwhile, the adjusted R^2 is 3.86% (0.93%) for high (low) volatility periods. The results in these two panels therefore lend support to the notion that information is the driving force of SSE's predictive power.

Finally, we examine the variation of the predictive power of SSE related to information environment. If SSE captures superior information about mispricing, we expect particularly strong return predictability in months with less public information since otherwise mispricing would have been corrected with more public information. For the cross-section of stocks, Cohen, Diether, and Malloy (2007) show that short selling demand has better predictive ability for stock returns when there is less public information. Our analysis in essence is similar to their investigation, though we focus on return predictability of the aggregate stock market rather than individual stocks. As such, we define high information months as the first two months (e.g., January and February) of each quarter, since earnings announcements are more prevalent in these months.[12] Accordingly, low information months are the last month of each quarter. We test the predictive power for excess market returns following high and low information months separately.

Panel C of Table 9 reports the predictive power of SSE during high and low public information months. To forecast the equity premium of month t + 1, we measure SSE and the information-month status in month t. The regression coefficient on SSE is -1.00 (t-value = -2.95) in low information months, compared with -0.43 (t-value = -2.12) in high information months. The test for the difference in the coefficient between high and low information months shows a p-value of 0.06. Furthermore, the adjusted R^2 is much larger for months with low public information than for months with high public information. Relatedly, the first month of each quarter (i.e., January, April, July, and October) is also the period when quarterly earnings announcements first appear

[12] See, e.g., Frazzini and Lamont (2006) and Hartzmark and Solomon (2018) for evidence of seasonality in earnings announcements at the firm level.

and mispricing gets corrected, contributing to the strong return predictability. These results thus provide further support to the information-based explanation for the predictive power of SSE.

Taken as a whole, the findings lend support to the view that SSE reflects information advantage of short sellers, as the predictive power appears particularly strong when information acquisition should be valuable. Our tests complement existing research about the cross-section of stocks (e.g., Cohen, Diether, and Malloy, 2007; Boehmer, Jones, and Zhang, 2008; Engelberg, Reed, and Ringgenberg, 2012) and provide new evidence that short sellers are informed.

6.2. Evidence from daily data

In this subsection, we provide further evidence of the predictive ability of SSE based on daily data. We construct daily SSE using the daily short selling data obtained from Markit, Ltd. Our sample begins in July 2006 when the data became available at daily frequency and extends to March 2011. We again exclude the crisis period July 2008–January 2009 (the period of market crash which covers the short-sale ban).[13] For each stock in day t, daily abnormal short interest (ASI) is defined as the difference of short interest in the day and the average short interest in the past 30 days. In each cross-section, stocks are ranked from 1 to 100 based on their mispricing scores at the beginning of the month, with a large (small) score indicating overpricing (underpricing). We require the stocks in our sample to have non-missing values of ASI and the mispricing score. Then, we regress ASI on the demeaned mispricing ranks in each day to compute daily SSE based on the slope coefficient. In the test of forecasting power, the daily SSE is the average in the past five days and standardized. We exclude micro-cap stocks and stocks whose prices are less than five dollars at the beginning of the month.

Figure 2 shows the daily evidence. The y-axis is the coefficient from regressing future cumulative excess market returns on the daily SSE. The x-axis is the number of days, from one up to 15 trading days, into the future. We observe a steady negative coefficient over the different horizons of days, suggesting that the daily SSE is negatively associated with future cumulative

[13] The security lending data may not reflect short selling by option market makers during the short-sale ban.

stock market returns. The confidence band confirms statistical significance of the negative relation between daily SSE and future market returns. In addition, the relation extends to 15 trading days with no reversal. This evidence suggests that the predictive ability of SSE is more likely to reflect information advantage rather than short-term price impact of short selling, which corroborates with the earlier findings about the source of the predictive power of SSE. Figure 2 remains similar if we skip the first day in the predictive regressions to account for possible bid-ask bounce and other market microstructure noises.

[Insert Figure 2 about here.]

6.3. SSE and performance of the CAPM

Short sellers as a group attempt to exploit overpricing, and thus their trading can in turn relate to asset prices in equilibrium. In this section, we investigate the relation between SSE and performance of the CAPM (Sharpe, 1964; Lintner, 1965). The CAPM predicts that expected returns on individual stocks are positively and linearly related to their betas to aggregate price movement in equilibrium, manifested in a positive slope of the security market line. Despite being an influential model, the CAPM has faced serious challenges in empirical work, in that stock data fail to produce a positive-sloped security market line.

Could short selling be related to the performance of the CAPM? We hypothesize that the CAPM performs well when SSE is low, given our finding that a high level of SSE signals relative prevalence of overpricing. To test the hypothesis, we divide the sample into two subperiods depending on whether the value of SSE in each month is above or below its time-series median. We are interested in how the CAPM fares in high versus low SSE periods.

Figure 3 shows the results about the security market line. We first estimate the CAPM beta for each individual stock over the entire sample period. Then, each month we form ten decile portfolios of stocks based on the CAPM beta. Next, we compute value-weighted average returns for each decile portfolio in the next month. In the figure, each dot corresponds to the average next month return of a decile portfolio formed in a particular subperiod. Following the low-SSE subperiod, the portfolio of lowest-beta stocks exhibits a market beta of 0.56 and a value-weighted average return of 0.86% per month, whereas the portfolio of highest-beta stocks has a market beta of 1.65 and a value-weighted average return of 1.84% per month. Based on betas and returns of the ten portfolios, the security market line, shown as the upper fitted line, has a positive slope of 0.89 (t-value = 11.09), consistent with the CAPM. However, following the high-SSE subperiod, the security market line, shown as the lower fitted line, has a negative slope of -0.56 (t-value = -6.15), deviating from the CAPM's prediction. Such a stark contrast suggests that the CAPM tends to hold only when SSE is low. We find the same inference when examining equal-weighted average returns for the decile portfolios.

[Insert Figure 3 about here.]

The result seems sensible. Building on the assumption that all investors are equally informed, the CAPM can fail to fit data in the presence of substantial information asymmetry. Indeed, as theorized by Grossman and Stiglitz (1980), investors are asymmetrically informed due to differential costs in gathering information. Empirically, Chen, Kelly, and Wu (2020) show that sophisticated investors such as hedge funds and short sellers have comparative advantage over other types of institutional investors in information acquisition. To the extent that short sellers collect and process information better than other investors, we expect the CAPM to perform poorly when short selling is efficient. In contrast, a positive-sloped security market line tends to emerge following low SSE.

In sum, we show that SSE serves as an important condition for the validity of the CAPM. Recent research finds that the CAPM behaves well under certain market circumstances, such as macroeconomic announcement days (Savor and Wilson, 2014), pessimistic sentiment (Antoniou, Doukas, and Subrahmanyam, 2016), and low margin requirement (Jylha, 2018). Our study provides novel evidence on how short selling efficiency relates to performance of the CAPM and hence stock market efficiency.

7. Conclusion

In this paper, we explore the economic insight that how efficiently short selling is allocated across stocks should affect future price movement at the aggregate level. We propose a measure of short selling efficiency (SSE) using the slope coefficient of a cross-sectional regression of abnormal short interest on the mispricing score, which captures the extent that short selling is aligned with overpricing. Our comprehensive analyses show that SSE contains significant and robust forecasting signals for aggregate stock returns. The forecasting signals of SSE are distinct from those of aggregate short selling studied by Rapach, Ringgenberg, and Zhou (2016). We argue conceptually and show empirically that SSE has favorable predictive ability over aggregate short interest, as SSE reduces the effect of noises in short interest. Since constructing the SSE measure only requires short interest and a mispricing score of stocks, both of which are readily available, our results also provide useful asset-allocation guidance to practitioners.

Furthermore, we show that short selling efficiency relates to the performance of the CAPM that describes the stock beta–return relation in the cross-section. Following periods with low SSE, the CAPM works well in that a significantly positive relation between beta and stock returns is observed. However, the security market line appears to be downward sloping following periods with high SSE. This finding confirms that arbitrage activity is related to equilibrium asset prices and stock market efficiency.

For future research, one could consider examining whether the time-variation in SSE can serve as a systematic factor, the exposure to which affects expected stock return. It would also be interesting to extend our investigation to international markets, where both short selling and stock mispricing vary across countries.

Appendix A

In this section, we illustrate the economic mechanism behind the predictability of SSE and SSL using a stylized model of short interest. We assume that short interest (SI) on stock i in month t takes the following form:

$$SI_{i,t} = \max(m_t + a \times MISP_{i,t}, 0) + \varepsilon_{i,t}, \quad \text{(A.1)}$$

where m_t represents the overall absolute mispricing at the market level in month t. $MISP_{i,t}$ is the stock-level mispricing score of Stambaugh, Yu and Yuan (2015), normalized to be uniformly distributed between -0.5 and 0.5, so 0.5 (-0.5) indicates the most overpriced (underpriced) stock in the cross-section. a is a constant scaling factor to make market-level absolute mispricing and cross-sectional relative mispricing comparable. The max operator is required since informed short sellers should short overpriced stocks only. We assume $-0.5a < m_t < 0.5a$ to rule out the extreme case that all stocks are overpriced (or underpriced). As a result, mispricing-driven short interest is positive for some stocks but is truncated to zero for other stocks in the cross-section. Aggregate mispricing m_t negatively predicts future market returns when the mispricing is corrected.

We further introduce a positive noise term to short interest, $\varepsilon_{i,t}$, to capture additional demand for short selling that is unrelated to absolute overpricing of the stock. For instance, such demand could reflect hedging positions related to convertible bonds, options, or ETFs. For simplicity, we assume $\varepsilon_{i,t}$ to be i.i.d. uniformly distributed in $[0, 2\varepsilon_t]$. At the portfolio level, by the law of large numbers, the portfolio's average noise is equal to ε_t which can vary over time. For example, increased supply of lendable shares (e.g., due to expanded institutional ownership) can increase shorting activity for all stocks. Without loss of generality, we assume that all individual stocks have a noise term equal to ε_t. Alternatively, we can examine portfolios of stocks formed on MISP instead of individual stocks.

Figure A.1 below plots short interest as a function of MISP for a cross-section of stocks in a given month t.

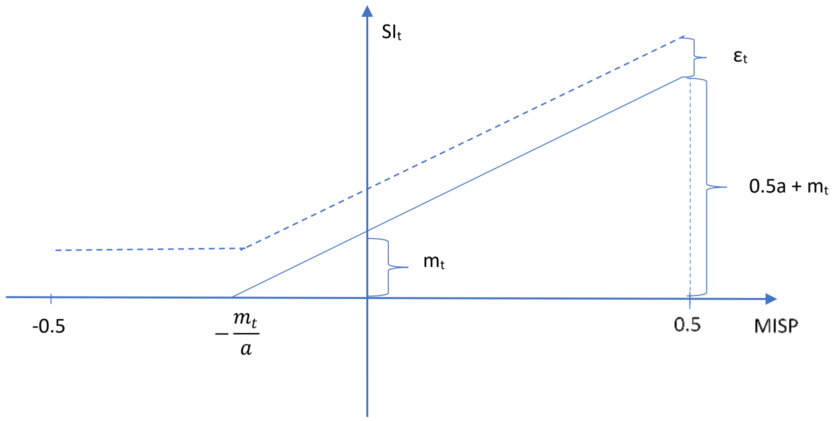

Figure A.1 The relation between short interest (SI) and the mispricing score (MISP). In the figure, $MISP_{i,t}$ is the stock-level mispricing score of Stambaugh, Yu and Yuan (2015) and normalized to be uniformly distributed between -0.5 and 0.5, with 0.5 (-0.5) indicating the most overpriced (underpriced) stock in the cross-section. Short interest on stock i in month t is assumed to take the following form: $SI_{i,t} = \max(m_t + a \times MISP_{i,t}, 0) + \varepsilon_{i,t}$. m_t represents the overall absolute mispricing at the market level in month t. a is a constant scaling factor to make market-level absolute mispricing and cross-sectional relative mispricing comparable. The max operator reflects the fact that informed short sellers should short overpriced stocks only. We assume -0.5a < mt < 0.5a to rule out the extreme case that all stocks are overpriced or underpriced. $\varepsilon_{i,t}$ is a positive noise term to short interest and captures additional demand for short selling that is unrelated to absolute overpricing of the stock. For simplicity, $\varepsilon_{i,t}$ is assumed to be i.i.d. uniformly distributed in $[0, 2\varepsilon_t]$.

The mispricing-driven short interest (i.e., $\max(m_t + a \times MISP_{t,i}, 0)$) is represented by the solid line that is truncated at MISP = $-m_t/a$. The noise term shifts the line up by ε_t so that the dashed line represents the observed short interest.

Under this simple framework, short interest level (SSL) at the market level can be computed as the area under the dashed line.

$$SSL_t = \frac{(0.5a+m_t)\left(0.5+\frac{m_t}{a}\right)}{2} + \varepsilon_t$$

$$= \frac{a\left(0.5+\frac{m_t}{a}\right)^2}{2} + \varepsilon_t. \tag{A.2}$$

It can be verified that SSL is always increasing in m_t under our assumption that $-0.5a < m_t < 0.5a$, and thus SSL proxies for market-level mispricing with a noise due to ε_t.

In contrast, as ε_t is a constant in the cross-section, it will not appear in the calculation of short sell efficiency (SSE).

$$\text{SSE}_t = \frac{Cov(SI,MISP)}{Var(MISP)}, \quad \text{where } SI = \begin{cases} \varepsilon & if\ MISP < -\frac{m}{a}, \\ m + a \times MISP + \varepsilon & if\ MISP \geq -\frac{m}{a}. \end{cases} \tag{A.3}$$

Algebraic manipulation shows that

$$\text{SSE} = 0.5a + 1.5m - \frac{2}{a^2}m^3. \tag{A.4}$$

We verify that SSE is always increasing in m_t so long as -0.5a < m_t < 0.5a. As result, SSE proxies for market-level mispricing. The intuition is simple. A higher m_t means that more stocks are overpriced in the cross-section. Since short sellers are informed, they correctly devote more capital to the more overpriced stocks, consistent with Hanson and Sunderam (2014). Both forces work together to increase the covariance between SI and MISP and hence SSE. The advantage of SSE over SSL is that it is not affected by the noise term ε_t.

To further see the intuition, we can examine short interest on two portfolios. O represents short interest on the top decile of stocks that are most overpriced, and U represents short interest on the bottom decile of stocks that are most underpriced. Without loss of generality, we assume that none of the stocks in the bottom decile is overpriced in absolute term. It is easy to show that

$$\text{O} = (m_t + 0.45a) \times 0.1 + \varepsilon_t, \tag{A.5}$$

$$\text{and} \quad \text{U} = \varepsilon_t. \tag{A.6}$$

In this case, O+U, equal to $(m_t + 0.45a) \times 0.1 + 2\varepsilon_t$, is similar to SSL. It is increasing in m_t but is also affected by the noise term ε_t. Meanwhile, O-U, equal to $(m_t + 0.45a) \times 0.1$, is akin to SSE. Note that O-U is not affected by ε_t as the noise term is cancelled out when we focus on the difference between O and U. That is,

$$\text{O + U} = (m_t + 0.45a) \times 0.1 + 2\varepsilon_t, \tag{A.7}$$

$$\text{and} \quad \text{O – U} = (m_t + 0.45a) \times 0.1. \tag{A.8}$$

In addition, O-U can be viewed as an alternative SSE measure that does not require mispricing to be a linear function of MISP across all stocks. Instead, it only requires that stocks in the bottom MISP decile are not overpriced in absolute term and stocks in the top MISP decile are overpriced, especially when the aggregate overpricing is high, so O-U reveals aggregate overpricing (m_t).

Finally, SSE, or O-U, can even predict future returns on the most underpriced stocks. This is because a low SSE indicates overall market underpricing ($m_t < 0$), more so for stocks in the bottom MISP decile. Thus, when such underpricing gets corrected in the future, these stocks will earn higher future returns, resulting in a negative relation between SSE today and future returns.

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Table 1 Summary Statistics

This table presents summary statistics of SSE and other return predictors in time series. For each stock in month t, abnormal short interest (ASI) is defined as the difference of short interest in the month and the average short interest in the past 12 months. In each cross-section, stocks are ranked from 1 to 100 based on their mispricing scores, with a large (small) score indicating overpricing (underpricing). We require the stocks in our sample to have non-missing values of ASI and mispricing score. We demean these mispricing ranks and then regress ASI on these demeaned mispricing ranks in each month to compute SSE (the slope coefficient) and short selling level SSL (the intercept). We remove time trend and standardize both SSE and SSL. In the main analysis, we exclude micro-cap stocks and stocks whose prices are less than five dollars at the time of portfolio formation. Other return predictors include sentiment (SENT), price-earnings ratio (PE), price-dividend ratio (PD), credit spread (CS), term spread (TS), the three-month T-bill rate (TB3M), funding liquidity (FLS), capital ratio (CAPR), long-term bond return (LTR), and return volatility (RVOL). These variables are described in detail in Section 3.2. All the variables except price multiples are multiplied by 100. Panel A presents summary statistics, while Panel B reports correlations among the variables. AR1 is the first-order autocorrelation. The sample period is from January 1974 to December 2017.

Panel A: Summary of the predictors

	Mean	Median	Std. Dev.	5th	25th	75th	95th	AR1
SSE	0.00	-11.25	100.00	-149.29	-54.08	42.98	174.92	0.84
SSL	0.00	-6.38	100.00	-115.62	-23.41	26.65	136.23	0.91
SENT	3.19	7.32	89.55	-189.27	-24.54	53.72	128.72	0.98
PE	20.24	20.50	8.86	8.74	11.60	25.96	37.28	1.00
PD	41.70	37.86	17.83	19.04	26.23	53.40	76.69	1.00
CS	1.10	0.96	0.46	0.61	0.77	1.29	2.03	0.96
TS	0.75	0.71	0.73	-0.34	0.18	1.30	2.02	0.98
TB3M	5.72	5.83	3.61	0.64	2.44	8.03	12.62	1.00
FLS	0.91	0.97	3.88	-4.96	-1.08	3.16	6.63	0.17
CAPR	6.15	5.33	2.46	3.33	4.36	7.63	11.64	0.99
LTR	0.72	0.77	3.12	-4.35	-1.17	2.48	5.82	0.05
RVOL	4.06	4.02	1.60	1.73	2.84	4.96	7.55	0.96

Panel B: Correlations

	SSE	SSL	SENT	PE	PD	CS	TS	TB3M	FLS	CAPR	LTR
SSL	0.60										
SENT	0.09	0.22									
PE	0.08	0.14	0.34								
PD	0.12	0.17	0.34	0.96							
CS	-0.11	-0.26	-0.10	-0.54	-0.46						
TS	-0.12	-0.15	-0.03	0.12	0.20	0.00					
TB3M	0.01	0.05	0.09	-0.59	-0.61	0.31	-0.70				
FLS	-0.11	-0.12	0.03	0.01	0.00	-0.04	0.06	-0.01			
CAPR	0.11	0.20	0.36	0.88	0.85	-0.54	-0.07	-0.29	0.07		
LTR	0.03	0.03	0.04	-0.04	-0.04	0.10	0.02	0.04	-0.21	-0.03	
RVOL	-0.03	-0.23	-0.21	-0.18	-0.10	0.46	0.06	0.12	-0.02	-0.14	0.02

Table 2 Forecasting Excess Market Returns: Univariate Regression

This table reports the predictive power of SSE and other return predictors in a univariate regression at the one-, three-, six- and 12-month horizons in Panels A through D, respectively. The other return predictors include short selling level (SSL), sentiment (SENT), price-earnings ratio (PE), price-dividend ratio (PD), credit spread (CS), term spread (TS), the three-month T-bill rate (TB3M), funding liquidity (FLS), capital ratio (CAPR), long-term bond return (LTR), and return volatility (RVOL). The dependent variable is monthly excess market return. Coeff is the regression coefficient on the return predictor, t-value is the Newey-West t-value with eight lags, and R^2 is the adjusted R-squared. The regression coefficients are multiplied by 100.

	SSE	SSL	SENT	PE	PD	CS	TS	TB3M	FLS	CAPR	LTR	RVOL
Panel A: Forecasting one-month return												
Coeff	-0.61	-0.22	-0.21	-0.02	-0.01	38.01	38.47	-5.91	-2.30	-10.50	12.46	17.60
t-value	-3.50	-1.34	-0.81	-0.77	-1.10	0.61	1.38	-1.04	-0.28	-1.16	2.20	1.73
R^2 (%)	1.64	0.05	-0.01	-0.07	0.08	-0.04	0.20	0.03	-0.15	0.13	0.55	0.20
Panel B: Forecasting three-month return												
Coeff	-0.64	-0.43	-0.20	-0.02	-0.01	46.55	34.18	-4.64	-0.77	-10.82	6.14	16.85
t-value	-3.27	-2.83	-0.84	-0.90	-1.25	0.85	1.34	-0.85	-0.11	-1.29	1.28	1.75
R^2 (%)	5.30	2.38	0.25	0.25	0.67	0.45	0.68	0.20	-0.18	0.78	0.32	0.81
Panel C: Forecasting six-month return												
Coeff	-0.62	-0.56	-0.25	-0.02	-0.02	62.53	28.92	-3.74	-0.85	-10.59	7.95	13.11
t-value	-3.56	-3.54	-1.20	-1.15	-1.50	1.45	1.28	-0.70	-0.22	-1.36	2.59	1.54
R^2 (%)	9.45	7.99	1.10	1.02	1.85	2.01	1.00	0.29	-0.16	1.58	1.43	0.94
Panel D: Forecasting 12-month return												
Coeff	-0.40	-0.45	-0.23	-0.03	-0.02	47.17	25.68	-2.27	-1.13	-9.51	4.68	7.93
t-value	-3.69	-3.92	-1.38	-1.50	-1.87	1.45	1.42	-0.49	-0.58	-1.44	2.74	1.11
R^2 (%)	8.49	10.96	2.15	3.07	4.58	2.48	1.83	0.18	-0.09	2.91	1.02	0.68

Table 3 Forecasting Excess Market Returns: Bivariate Regression

This table reports the predictive power of SSE along with other return predictors, one at a time, in bivariate regressions at the one-, three-, six- and 12-month horizons in Panels A through D, respectively. The other return predictors include short selling level (SSL), sentiment (SENT), price-earnings ratio (PE), price-dividend ratio (PD), credit spread (CS), term spread (TS), the three-month T-bill rate (TB3M), funding liquidity (FLS), capital ratio (CAPR), long-term bond return (LTR), and return volatility (RVOL). In each panel, the top two lines correspond to SSE, while the next two lines correspond to one other predictor in each column. The dependent variable is monthly excess market return. Coeff is the regression coefficient on the return predictor, t-value is the Newey-West t-value with eight lags, and R^2 is the adjusted R-squared. The regression coefficients are multiplied by 100.

		SSL	SENT	PE	PD	CS	TS	TB3M	FLS	CAPR	LTR	RVOL
Panel A: Forecasting one-month return												
SSE	Coeff	-0.75	-0.60	-0.60	-0.56	-0.60	-0.59	-0.61	-0.63	-0.59	-0.62	-0.60
	t-value	-3.03	-3.41	-3.48	-2.91	-3.32	-3.25	-3.55	-3.63	-3.22	-3.53	-3.36
Other predictor	Coeff	0.22	-0.15	-0.01	1.65	23.13	29.07	-5.73	-3.94	-7.96	12.99	16.34
	t-value	0.90	-0.60	-0.54	1.33	0.36	1.02	-1.02	-0.51	-0.94	2.34	1.74
	R^2 (%)	1.61	1.54	1.51	1.84	1.51	1.68	1.66	1.57	1.52	2.26	1.79
Panel B: Forecasting three-month return												
SSE	Coeff	-0.59	-0.63	-0.63	-0.61	-0.62	-0.62	-0.64	-0.65	-0.61	-0.64	-0.63
	t-value	-2.70	-3.19	-3.23	-3.10	-3.05	-3.02	-3.29	-3.43	-3.03	-3.31	-3.15
Other predictor	Coeff	-0.08	-0.13	-0.01	1.09	29.86	24.11	-4.66	-2.57	-8.17	6.64	14.77
	t-value	-0.39	-0.59	-0.61	0.99	0.53	0.91	-0.88	-0.41	-1.04	1.41	1.67
	R^2 (%)	5.18	5.32	5.30	5.73	5.38	5.55	5.51	5.26	5.45	5.72	5.88
Panel C: Forecasting six-month return												
SSE	Coeff	-0.43	-0.60	-0.60	-0.60	-0.59	-0.60	-0.62	-0.63	-0.59	-0.62	-0.61
	t-value	-2.46	-3.48	-3.54	-3.46	-3.37	-3.28	-3.55	-3.71	-3.36	-3.61	-3.48
Other predictor	Coeff	-0.30	-0.19	-0.02	0.73	46.14	19.14	-3.86	-2.54	-8.02	8.39	10.77
	t-value	-1.49	-0.98	-0.83	0.87	1.11	0.81	-0.75	-0.77	-1.09	2.81	1.43
	R^2 (%)	10.79	9.99	9.87	9.91	10.45	9.79	9.78	9.52	10.04	11.08	10.03
Panel D: Forecasting 12-month return												
SSE	Coeff	-0.20	-0.39	-0.38	-0.37	-0.38	-0.38	-0.40	-0.41	-0.38	-0.41	-0.39
	t-value	-1.48	-3.65	-3.66	-3.23	-3.53	-3.20	-3.65	-3.83	-3.51	-3.74	-3.56
Other predictor	Coeff	-0.33	-0.19	-0.02	0.88	35.79	19.52	-2.48	-2.28	-7.88	4.96	6.03
	t-value	-2.09	-1.27	-1.24	1.07	1.19	1.03	-0.57	-1.38	-1.24	3.06	0.97
	R^2 (%)	12.16	9.93	10.46	9.62	9.83	9.47	8.76	8.75	10.28	9.68	8.82

Table 4 Forecasting Excess Market Returns: Multivariate Regression

This table reports the predictive power of SSE along with additional control variables in multivariate regressions at the one-, three-, six- and 12-month horizons in Panels A through D, respectively. The control variables include the short interest index (SII) of Rapach, Ringgenberg, and Zhou (2016), short selling level (SSL), 10 return predictors including sentiment, price-earnings ratio, price-dividend ratio, credit spread, term spread, the three-month T-bill rate, funding liquidity, capital ratio, long-term bond return, and return volatility, and 11 aggregate stock anomalies including financial distress, o-score bankruptcy probability, net stock issues, composite equity issues, total accruals, net operating assets, momentum, gross profitability, asset growth, return on assets, and investment to assets. In each panel, the first two columns include the 10 return predictors, and the third column includes the 11 aggregate stock anomalies. The dependent variable is monthly excess market return. Coeff is the regression coefficient on the return predictor, t-value is the Newey-West t-value with eight lags, and R^2 is the adjusted R-squared. The regression coefficients are multiplied by 100. The monthly SII data span till December 2014.

		1974–2014	1974–2017	1974–2017	1974–2014	1974–2017	1974–2017
		Panel A: Forecasting one-month return			Panel B: Forecasting three-month return		
SSE	Coeff	-0.48	-0.80	-0.80	-0.45	-0.62	-0.59
	t-value	-2.34	-3.00	-3.28	-2.16	-2.71	-2.84
SII	Coeff	-0.27			-0.34		
	t-value	-1.18			-1.59		
SSL	Coeff		0.47	0.40		0.11	0.03
	t-value		1.73	1.61		0.43	0.16
	R^2 (%)	2.54	2.61	3.30	9.79	8.01	12.90
additional predictors		10 return predictors	10 return predictors	11 stock anomalies	10 return predictors	10 return predictors	11 stock anomalies
		Panel C: Forecasting six-month return			Panel D: Forecasting 12-month return		
SSE	Coeff	-0.43	-0.45	-0.42	-0.16	-0.18	-0.18
	t-value	-2.80	-2.49	-2.47	-1.65	-1.34	-1.34
SII	Coeff	-0.33			-0.38		
	t-value	-1.69			-2.47		
SSL	Coeff		-0.16	-0.20		-0.24	-0.21
	t-value		-0.57	-0.94		-1.22	-1.20
	R^2 (%)	19.94	16.88	23.26	26.44	22.38	33.87
additional predictors		10 return predictors	10 return predictors	11 stock anomalies	10 return predictors	10 return predictors	11 stock anomalies

Table 5 Out-of-Sample Predictability

This table reports the out-of-sample predictability. We test the forecasting power of each predictor for one-month-ahead stock market returns. First, we run the following time-series regression:

$$r_t = \alpha + \beta x_{t-1} + \varepsilon_t,$$

where r_t is excess market return for month t, and x_{t-1} is one-month lagged value of the predictor. Then, based on the regression coefficient estimates only using information up to month t, we compute the forecast of the equity premium for month t+1. We either expand the subsample by one month each time (expanding approach) or use a 10-year rolling window (rolling approach) to generate the time series of equity premium forecast, i.e., $\hat{r}_{t+1}, \hat{r}_{t+2}, \ldots, \hat{r}_T$. The out-of-sample R^2 compares the mean-squared errors obtained from the predictor with those from the historical average.

$$R^2 = 1 - \frac{\sum_{\tau=t+1}^{T}(r_\tau - \hat{r}_\tau)^2}{\sum_{\tau=t+1}^{T}(r_\tau - \bar{r}_\tau)^2},$$

where $\bar{r}_\tau$ is the historical average of excess market returns up to month τ - 1, and T is the total number of months over the entire sample period. A positive out-of-sample R^2 indicates outperformance of the predictor over the historical average. We winsorize SSE and SSL at 1% and 99% and remove their time trend stochastically by only using information up to month t. Specifically, we use the sample from January 1974 to December 1975 as the first subsample to remove the time trend. Then, we standardize the residuals of the time-trend regression and retain the last observation. We extend the subsample by one month at a time. Our initial regression uses data of 10 years (January 1976–December 1985), and thus the out-of-sample prediction for excess stock market returns starts in January 1986. In each approach (expanding or rolling), we consider three cases of economic restrictions. Case 1 imposes no restriction. Cases 2 imposes the coefficient sign restriction, which sets an equity premium forecast to the historical average when the coefficient sign is incorrect. Case 3 imposes the premium sign restriction, which sets an equity premium forecast to zero when the forecast value is negative. We compute p-values (p1, p2, and p3) based on the Clark and West (2007) method. The predictors include short selling efficiency (SSE), short selling level (SSL), sentiment (SENT), price-earnings ratio (PE), price-dividend ratio (PD), credit spread (CS), term spread (TS), the three-month T-bill rate (TB3M), funding liquidity (FLS), capital ratio (CAPR), long-term bond return (LTR), and return volatility (RVOL).

Table 5, continued.

		Case 1	Case 2	Case 3	p1	p2	p3
SSE	Expanding	1.17	1.41	0.99	0.04	0.02	0.04
	Rolling	1.38	1.67	1.03	0.03	0.02	0.02
SSL	Expanding	0.33	0.44	0.33	0.15	0.09	0.15
	Rolling	0.84	1.03	0.68	0.06	0.04	0.07
SENT	Expanding	0.17	0.23	0.17	0.22	0.16	0.22
	Rolling	-0.09	0.07	0.95	0.15	0.13	0.06
PE	Expanding	-2.21	-1.72	-1.41	0.89	0.81	0.85
	Rolling	-2.59	-1.68	-1.48	0.73	0.49	0.53
PD	Expanding	-1.90	-1.37	-1.41	0.79	0.64	0.73
	Rolling	-3.67	-2.70	-1.80	0.78	0.58	0.57
CS	Expanding	-0.97	-0.74	-0.83	0.78	0.69	0.73
	Rolling	-2.69	-0.84	-0.15	0.42	0.56	0.23
TS	Expanding	-0.45	-0.43	-0.45	0.56	0.55	0.56
	Rolling	-0.89	-0.10	-0.51	0.65	0.35	0.52
TB3M	Expanding	-0.59	-0.53	-0.59	0.73	0.69	0.73
	Rolling	-1.14	-0.33	-0.27	0.44	0.27	0.25
FLS	Expanding	-1.07	-0.56	-0.95	0.86	0.72	0.84
	Rolling	-1.84	-1.24	-1.09	0.51	0.55	0.40
CAPR	Expanding	-0.98	-0.62	-0.66	0.57	0.40	0.55
	Rolling	-1.94	-1.31	-0.96	0.48	0.29	0.36
LTR	Expanding	0.06	0.06	0.24	0.24	0.24	0.17
	Rolling	0.69	0.56	1.07	0.04	0.06	0.01
RVOL	Expanding	-1.30	-1.30	-1.20	0.41	0.41	0.40
	Rolling	-2.09	-1.64	-1.55	0.68	0.56	0.53

Table 6 Predictive Power of SSE: Robustness Checks

This table reports several sets of robustness checks for the predictive power of SSE. Panel A reports the in-sample evidence of the predictive power of SSE for excess market returns at different horizons using predictive regressions. First, we examine the un-detrended SSE. Second, as an alternative measure of SSE, we examine the O-U spread in the average abnormal short interest between stocks in the top decile and those in the bottom decile of the Stambaugh, Yu, and Yuan (2015) mispricing score. Third, we include micro-cap stocks in the sample. Fourth, we include lagged values of volatility, trading volume, and stock return as additional control variables in Equation (1) when estimating SSE. Fifth, we exclude the period July 2008 to January 2009. The dependent variable is monthly excess market returns. The independent variables of interest are standardized. In tests (2) – (5), time trend is removed before the standardization. Coeff is the regression coefficient on the SSE, t-value is the Newey-West t-value with eight lags, and R^2 is the adjusted R-squared. The regression coefficients are multiplied by 100. Panel B reports the out-of-sample predictive power for one-month-ahead excess market returns. In tests (2) – (4), time trend is removed before the standardization. Panel C reports the out-of-sample predictive power of SSE for excess stock market returns at longer horizons, where SSE is the original measure. Finally, Panel D reports results from a bootstrap analysis. In an iteration, we resample stocks with replacement in the cross-section for each month and estimate SSE for the month. The time-series of SSE is detrended and standardized. We then draw blocks of three consecutive observations from the time-series of SSE and market returns. We use a block size of three because the BIC of an autoregressive process for the original SSE suggests two lags. Next, we run the predictive regression and record the regression coefficient on SSE. The iteration is then repeated 1,000 times. We report the average coefficient and adjusted R-squared across all iterations.

Panel A: In-sample predictability of alternative SSE measures					
	(1)	(2)	(3)	(4)	(5)
	Un-detrended SSE	O-U spread	Including microcap	SSE with controls	Excluding financial crisis
Forecasting one-month return					
Coeff	-0.47	-0.54	-0.55	-0.41	-0.59
t-value	-2.21	-3.48	-3.40	-2.45	-3.21
R^2 (%)	0.89	1.25	-1.31	0.62	1.47
Forecasting three-month return					
Coeff	-0.48	-0.54	-0.55	-0.40	-0.53
t-value	-2.33	-3.17	-3.41	-2.41	-3.19
R^2 (%)	3.03	3.87	3.96	2.00	3.56
Forecasting six-month return					
Coeff	-0.47	-0.54	-0.43	-0.39	-0.52
t-value	-2.57	-3.19	-2.97	-2.95	-3.40
R^2 (%)	5.66	7.45	4.67	3.76	6.37
Forecasting 12-month return					
Coeff	-0.31	-0.32	-0.27	-0.26	-0.38
t-value	-2.20	-2.93	-2.34	-2.92	-3.14
R^2 (%)	5.05	5.63	3.69	3.47	6.89

Table 6, continued.

Panel B: Out-of-sample predictability of alternative SSE measures

		Case 1	Case 2	Case 3	p1	p2	p3
(1) Undetrended SSE	Expanding	0.35	0.52	0.91	0.12	0.10	0.04
	Rolling	0.68	1.00	1.68	0.04	0.03	0.01
(2) O-U Spread	Expanding	0.86	0.87	0.89	0.07	0.06	0.05
	Rolling	0.79	0.80	0.62	0.05	0.04	0.03
(3) Including microcap	Expanding	0.8	1.12	0.81	0.05	0.02	0.05
	Rolling	0.26	1.01	0.49	0.05	0.01	0.03
(4) SSE with controls	Expanding	0.59	0.71	0.60	0.07	0.05	0.07
	Rolling	0.61	0.78	1.29	0.03	0.02	0.01

Panel C: Out-of-sample predictability of the original SSE measure at longer horizons

		Case 1	Case 2	Case 3	p1	p2	p3
Forecasting three-month return							
SSE	Expanding	1.53	3.34	1.35	0.06	0.01	0.06
	Rolling	2.64	4.47	1.97	0.01	0.00	0.02
Forecasting six-month return							
SSE	Expanding	5.26	6.04	4.90	0.01	0.00	0.01
	Rolling	6.26	7.88	3.92	0.01	0.00	0.03
Forecasting 12-month return							
SSE	Expanding	1.15	2.38	1.15	0.10	0.03	0.10
	Rolling	3.71	4.52	3.73	0.01	0.01	0.01

Panel D: Bootstrap analysis

	1-month	3-month	6-month	12-month
Coeff	-0.52	-0.56	-0.53	-0.35
p-value	0.01	0.00	0.00	0.00
R^2 (%)	1.36	4.68	7.37	6.70

Table 7 Understanding SSE and SSL

This table relates SSE and SSL to abnormal short interest (ASI) on mispriced stocks. The measure O is the abnormal short interest of overpriced stocks, calculated as the average ASI of stocks in the top decile portfolio formed on the mispricing score. Similarly, the measure U is the abnormal short interest of underpriced stocks, calculated as the average ASI of stocks in the bottom decile portfolio formed on the mispricing score. O+U is the sum of the two measures, while O-U is the difference of the two measures. All measures are time detrended. Panel A reports the correlations of the two measures with SSE and SSL. Panel B reports results of univariate regressions, in which we use O+U and O-U to forecast monthly excess returns of the portfolio of underpriced stocks and the portfolio of overpriced stocks, separately. Coeff is the regression coefficient on the return predictor, t-value is the Newey-West t-value with eight lags, and R^2 is the adjusted R-squared. The regression coefficients are multiplied by 100.

Panel A: Correlations

	SSE	SSL	O+U	O-U
SSE	1.00			
SSL	0.60	1.00		
O+U	0.64	0.97	1.00	
O-U	0.88	0.55	0.61	1.00

Panel B: Forecasting excess portfolio returns in univariate regressions

	Underpriced stocks		Overpriced stocks	
	O+U	O-U	O+U	O-U
Forecasting one-month return				
Coeff	-0.20	-0.39	-0.40	-0.68
t-value	-1.49	-3.00	-1.85	-3.20
R^2 (%)	0.03	0.70	0.37	1.44
Forecasting three-month return				
Coeff	-0.32	-0.41	-0.66	-0.70
t-value	-2.37	-2.93	-2.75	-2.97
R^2 (%)	1.68	2.79	4.01	4.55
Forecasting six-month return				
Coeff	-0.43	-0.44	-0.74	-0.65
t-value	-3.04	-3.21	-2.91	-2.76
R^2 (%)	6.08	6.23	9.80	7.48
Forecasting 12-month return				
Coeff	-0.34	-0.29	-0.49	-0.34
t-value	-3.36	-3.01	-2.94	-2.28
R^2 (%)	7.99	5.42	9.58	4.60

Table 8 Relation between SSE and AIO

This table examines the relation between short selling efficiency and abnormal institutional ownership (AIO) on stocks. AIO is the difference in institutional ownership of a stock between the current quarter end and its average in the past four quarters. The measure O is the average abnormal short interest (ASI) of overpriced stocks (i.e., those in the top decile portfolio formed on the mispricing score). The measure U is the average ASI of underpriced stocks (i.e., those in the bottom decile portfolio formed on the mispricing score). O+U (O-U) is the sum (difference) of the two measures. Panel A reports correlations. Panel B presents results from univariate predictive regressions. To compute predicted SSE, we first regress stock-level ASI on AIO each quarter and take the fitted value, and then we regress the fitted value on the mispricing score to construct predicted SSE for each quarter. Similarly, replacing the fitted value with residuals from the cross-sectional regression delivers residual SSE. The sample is at a quarterly frequency from 1981:Q1 to 2017:Q4 due to the data availability of institutional ownership. All predictors are time detrended. Returns are monthly averages in a given quarter. We use four lags to adjust for heteroscedasticity and autocorrelation in standard errors. The regression coefficients are multiplied by 100.

Panel A: Correlations

	AIO	O	U	O+U	O-U
AIO	1.00				
O	0.37	1.00			
U	0.30	0.81	1.00		
O+U	0.36	0.97	0.92	1.00	
O-U	0.29	0.79	0.28	0.62	1.00

Panel B: Forecasting excess market returns in univariate regressions

	Predicted SSE	Residual SSE
Q1 average monthly return		
Coeff	-0.11	-0.22
t-value	-1.26	-2.73
R^2 (%)	0.00	0.05
Q2 average monthly return		
Coeff	-0.32	-0.38
t-value	-1.90	-2.70
R^2 (%)	0.02	0.07
Q3 average monthly return		
Coeff	-0.47	-0.54
t-value	-1.97	-2.85
R^2 (%)	0.03	0.10
Q4 average monthly return		
Coeff	-0.50	-0.55
t-value	-1.68	-2.33
R^2 (%)	0.02	0.08

Table 9 Predictive Power of SSE: Conditional Evidence

This table reports conditional predictive power of SSE for excess market returns over the next month with respect to market conditions and information environment. Panel A examines the predictive power of SEE during normal times versus recessions. The recessions are based on the NBER recession indicators. We test the predictive power for excess stock market returns following normal times and recessions separately. In Panel B, we examine the predictive power of SSE during the months of high versus low market volatility. We split the sample into subperiods of high and low market volatility, depending on whether the value of VIX in a month exceeds the time-series median. Then, we test the predictive power for excess market returns following high and low volatility months separately. Finally, in Panel C, we examine the predictive power during months with high versus low level of public information. For each quarter, we define high information months as the first two months, since earnings announcements tend to occur in these months. Accordingly, low information months are the last month of each quarter. We then test the predictive power for excess market returns following high and low information months separately. In all the tests, we use univariate regressions to predict excess stock market returns at the one-month horizon (i.e., month t + 1), based on SSE and the conditional variables measured in month t. Coeff is the regression coefficient on SSE, t-value is Newey-West t-values with lags equal to the forecast horizon, and R^2 is the adjusted R-squared. The regression coefficients are multiplied by 100.

Panel A: NBER recessions

	Normal times	Recession times
Coeff	-0.43	-1.16
t-value	-2.32	-2.35
R^2 (%)	0.78	3.37
# of obs	457	70

Panel B: Market volatility

	Low volatility	High volatility
Coeff	-0.32	-1.15
t-value	-1.97	-2.49
R^2 (%)	0.93	3.86
# of obs	167	167

Panel C: Information environment

	High information	Low information
Coeff	-0.43	-1.00
t-value	-2.12	-2.95
R^2 (%)	0.79	3.11
# of obs	352	175

Figure 1 Time Series of Short Selling Efficiency

This figure plots short selling efficiency (SSE) over time. For each stock in month t, we first define abnormal short interest (ASI) as the difference of short interest in the month and the average of short interest in the past 12 months. We require the stocks in our sample to have non-missing values of ASI and the mispricing score. Each month, stocks are ranked from 1 to 100 based on their mispricing scores, with a large score representing overpricing. We demean these ranks in each cross-section. Then, from the regression of ASI on the demeaned mispricing ranks in each month, the slope coefficient is SSE while the intercept is short selling level (SSL). We remove time trend and standardize the values of SSE and SSL. Micro-cap stocks and stocks whose prices are less than five dollars are excluded. The sample period is from January 1974 to December 2017.

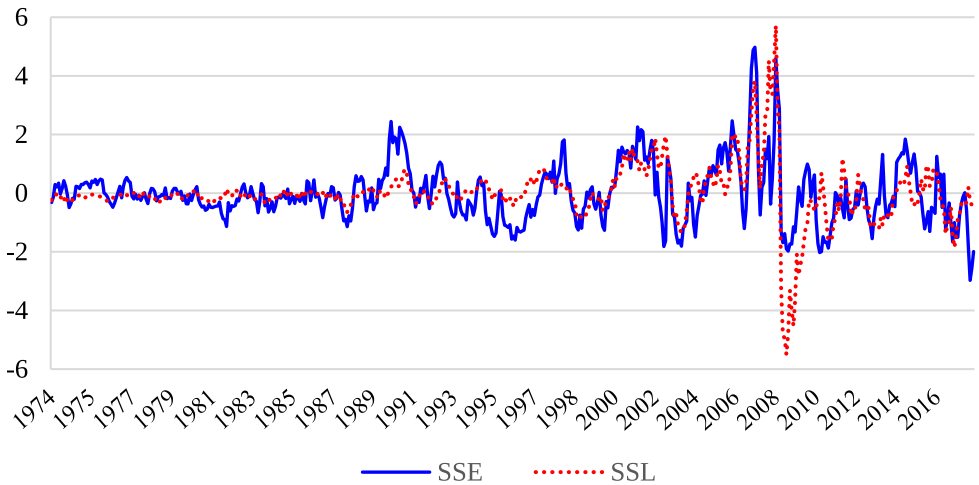

Figure 2 Predictive Power of SSE: Daily Evidence

This figure presents daily evidence of the predictive power of SSE. We construct daily SSE using the short selling data obtained from Markit. For each stock in day t, daily abnormal short interest (ASI) is defined as the difference of short interest in the day and the average short interest in the past 30 days. In each cross-section, stocks are ranked from 1 to 100 based on their mispricing scores at the beginning of the month, with a large (small) score indicating overpricing (underpricing). We require the stocks in our sample to have non-missing values of ASI and the mispricing score. We demean the mispricing ranks and then regress ASI on the demeaned mispricing ranks in each day to compute SSE based on the slope coefficient. In the test of forecasting power, the daily SSE is the average in the past five days and then standardized across stocks. We exclude micro-cap stocks and stocks whose prices are less than five dollars at the beginning of the month. In the figure, the y-axis is the coefficient from regressing future cumulative excess market returns on the daily SSE. The x-axis is the number of days into the future. The sample period is from July 2006 to March 2011, in which we exclude the period July 2008–January 2009.

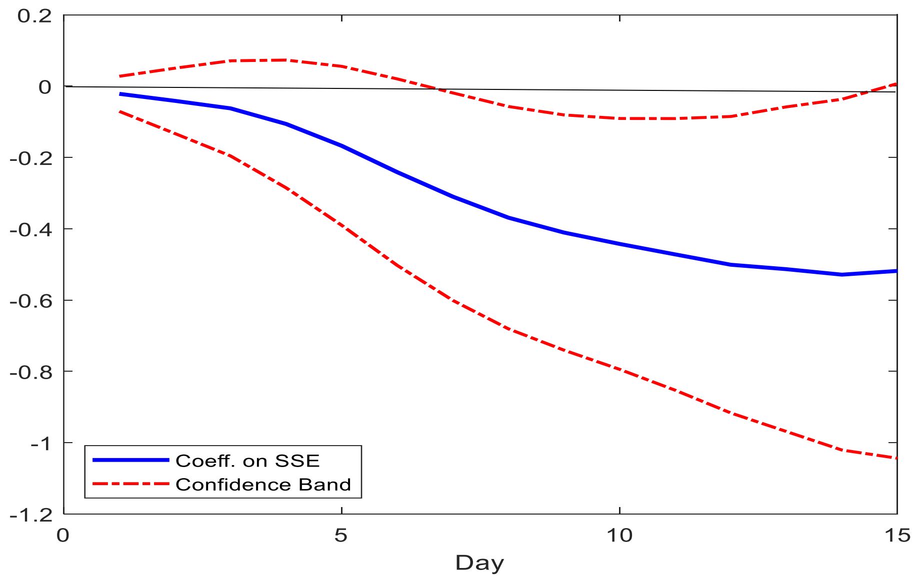

Figure 3 SSE and the Security Market Line

This graph plots the average returns of stock portfolios against the CAPM beta (i.e., the security market line) following subperiods of high versus low SSE (i.e., when SSE is above or below its time-series median level). We form decile stock portfolios based on the CAPM beta and plot the value-weighted average returns on the portfolios. Following each subperiod, we track the average return for each portfolio in the *subsequent* month. In the figure, each dot corresponds to the next-month average return for a beta portfolio following a particular subperiod. The average returns are in percent per month.